A

RESEARCH PROPOSAL

On

AN INVESTIGATION INTO HYBRID CONTROL SCHEME FOR ROBOTIC END EFFECTORS

For the degree of

DOCTOR OF PHILOSOPHY

By

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Table of Contents

1 Introduction 3
2 Literature Review 5
2.1 EMG control 7
2.2 EMG control schemes 7
2.3 Factors of influence of EMG 9
2.4 Implications in multi-functional control 9
3 Problem formulation and suggested solution 10
4 Objectives 12
5 Methodology 12
5.1 Work plan 13
6 References 14

1 Introduction

Since ancient times, engineers have been attempting to develop machines which could substitute humans performing complex, repetitive and hazardous actions. In the 19th century it was not possible to conceive devices able to execute a broad range of preset motion paths due to lack of programmable electronic logic. In those machines, mechanical elements such as levers, cams, gears, etc. were utilized as the only control scheme. However, with the introduction of programmable electronic logic, efficient control schemes were developed enabling the robots to perform sophisticated actions. Around 1970s, robotic manipulators were firstly introduced in the mass production lines to carry out heavy jobs, like soldering and pick-place tasks. The capabilities of moving heavy loads with fast and accurate dynamics and the programming flexibility were satisfactory since early stages. They presented limits, instead, to be adapted to different type of tasks, due to the inflexibility of terminal end-effectors that had to be designed for the particular application to accomplish.

With the growth of computational capacity and the miniaturizing of electronic components it became possible to foresee the development of general purpose end-effectors with the shape of human hands. The human hand is a result of million years of biological evolution that enables a person to perform tasks which no other living thing can ever perform. It is an ideal and most advanced end-effector in the world. Development of similar anthropomorphic end-effector for robots would allow to grasp and manipulate objects and tools just as humans do. However, the complexity involved in the design of such devices is relevant, since obtaining dexterity means having a high number of degrees of freedom (articulations) in a very compact space. Such a device would have to cover a large spectrum of manipulation movements such as power handling, delicate handling, gross movements, precision movements, etc. It implies the necessity to integrate within the hand a great number of suitable actuators and sensors in order to be able to feedback the state of the hand and then calculate and actuate the control action, according to the task being executed. Along with mechanical components, the control scheme of such end-effectors have to be competent enough to provide intuitive control, adaptive control, fast response time, and high degrees of freedom.

Robotic end-effectors with anthropomorphic characteristics together with effective control scheme, also let us consider the possibility to develop humanoid machines that can work out of the industrial environment and cooperate with humans, helping us in everyday tasks. Researchers have been prototyping over the years an impressive amount of robotic hands. Although many challenges have already been overcome, a large number of problems are yet to be addressed such as cost, reliability, computational complexity and intuitive control.

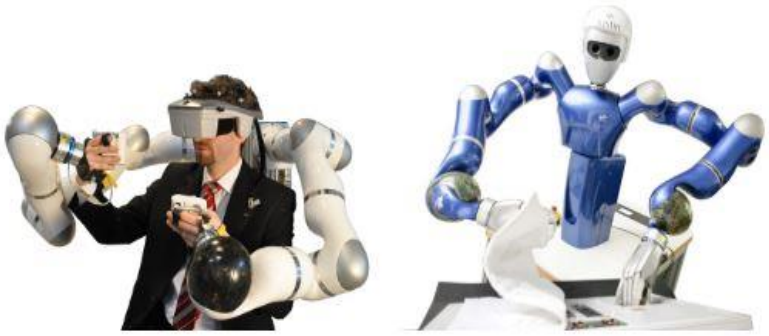
The control scheme for a robotic end-effector is affected by its field of application. Robotic end-effectors have been used for many decades in a number of application such – industrial, tele-manipulation, limb rehabilitation, service & care, etc. A robotic system consisting of single or multiple end-effectors have been used in industries for a variety of tasks ranging from manufacturing to final packaging. Different end-effectors are installed on an industrial robot for performing desired tasks. These industrial robotic systems are controlled through programmable logic controllers (PLC) which are programmed for specific actions.

Such systems are useful to carry out similar repetitive tasks and needs to be programmed for every new action. Assembly robots, welding robots, inspection probes, packaging systems, material handling robots, guided vehicle, object grippers etc. are some typical examples of such robotic systems (shown in Figure 1).

(a) Two fingers gripper (b) Three fingers gripper (c) Anthropomorphic gripper

Figure 1. Industrial robotic systems.

Robotic systems in tele-manipulation tasks tend to eliminate human interventions in hazardous and treacherous circumstances while maintaining the dexterity of human hand. It is accomplished through a tele-manipulation link between a controlling system (human operator) and a controlled system (robotic end-effector). Such systems are controlled through direct human-machine interfaces (HMI) in which a human operator controls the robot using buttons, joystick, switches, etc. In some instances, the devices are controlled through nervous system of the operator using – electromyography, mechanomyography, electroneurography, etc. techniques. Such techniques allows for a more intuitive control of end-effectors. Tele-manipulation robotic systems are used in variety of tasks such as providing support to astronauts, assistance in medical surgery, handling of nuclear waste and radioactive substances, etc. (shown in Figure 2 and Figure 3).



(a) Master: HUG (b) Slave: SpaceJustin

Figure 2. Tele-manipulation robotic systems.

Simple robotic end-effectors have been used since a long time for limb rehabilitation of an amputee. These robotic systems have features, grasps, and capabilities similar to a human hand. There are various techniques to control the prosthetic hand such as – electromyography, mechanomyography, electroneurography, etc. In these control schemes, signals from nervous system of a subject are utilized to actuate the artificial limb.

Robotic systems are also used for service and care application due to their capability to perform repetitive tasks precisely and with same efficiency every time. The trend of service robotic systems is projected towards developing robots for assisting human in a variety of tasks such as domestic, office, and taking care of necessities of children and the elderly. Some of service robotic systems are shown in Figure 4.

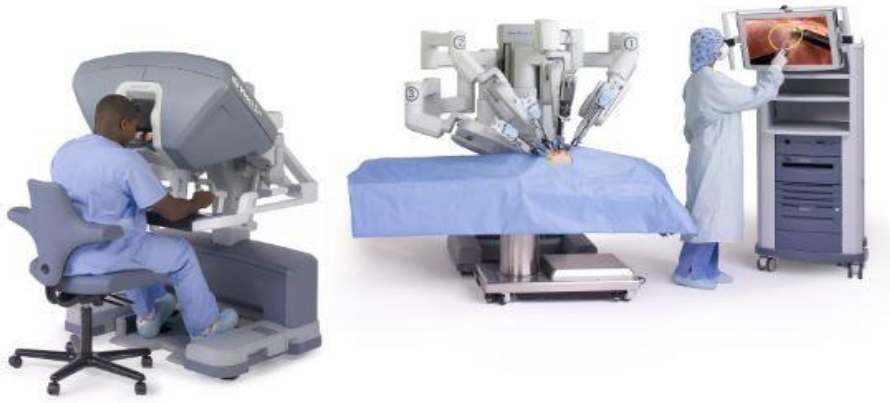


Figure 3. Tele-surgery robotic systems.

(a) Toro (DLR) (b) PR2 (WILLOW GARAGE) (c) Asimo (HONDA)

Figure 4. Humanoid robots.

Depending upon the area of application, a number of distinct control schemes have been developed for robotic end-effectors. They can either be programmed for similar repetitive tasks (e.g. welding robots, assembly robots), or manipulated directly for executing specialized tasks (e.g. nuclear material handling, science laboratories, etc.). The productivity of a robotic end-effector is directly linked to the efficiency of corresponding control scheme in each of the above mentioned applications. Therefore, it becomes important to develop a robust control scheme enabling an end-effector to perform specified tasks proficiently.

2 Literature Review

The control scheme of a robotic end-effector can be categorized as – intuitive and non-intuitive control. The non-intuitive control scheme utilize switches, joysticks, etc. for the movement and actuation of a robotic arm. On the other hand, in an intuitive control scheme a robotic arm is manipulated by using neural information from the nervous system of a human operator. The

intuitive control scheme utilizes signal extraction from the neuromuscular system of a human body through human-machine interfacing (HMI) [1].

The neural signals in this regards are extracted using invasive and noninvasive methods [2]. While invasive technique involve surgical procedures, noninvasive techniques extract peripheral information from neuromuscular system without any sophisticated procedures. The human-machine interface can be created at the levels of brain, peripheral nerves, or muscles [1]. Among these potential options, the muscle interfacing is currently the only viable way to control external devices as other techniques involve invasive procedures [3,4].

Despite the fact that muscle recordings are peripheral measurements and are not obtained directly from neural cells, they contain neural information on the executed motor tasks. Indeed, the electrical muscle signal, or electromyogram (EMG), contains similar information as direct efferent nerve recordings since there is a one-by-one association between action potentials travelling along the axon of each motor neuron and the compound action potential of the innervated muscle fibers (motor unit action potential). The surface EMG signal is thus strictly associated to the neural signal sent from the spinal cord to the muscles. It is obtained through electrodes connected to the surface of the hand of a subject. The notion of surface EMG recordings as sources of neural information is emphasized by the emerging procedure of targeted muscle reinnervation (TMR). In this technique nerves reaching the missing limb muscles are redirected to innervate accessory muscles, from which the motion intent of the subjects can be inferred [13].

The surface EMG is extensively used for human-machine interfacing (HMI) to control robotic end-effectors. It is because of its noninvasiveness, relative easy application, and richness of neural information. Despite the rather direct relation between a motion (or an intended motion) and the expressed EMG signal, however, there remain several open issues before the control of robotic end-effectors by EMG (myoelectric control) needed for widespread acceptance. Comparison of various methods for controlling a robotic hand is shown in Table 1.

Table 1. Comparison of various intuitive control methods [2].

Technique	Advantages	Limitations
Surface EMG	Non-invasive, ease of application	Non-natural control movements, influenced by physiological and environmental factors
Implantable EMG	Improved quality of EMG signals	Requires surgical implants
Targeted muscle reinnervation (TMR)	Natural control movements, effective sensory feedback	Requires sophisticated surgical procedures

2.1 EMG control

EMG signals that are recorded using surface electrodes (sEMG) represent a noninvasive method to measure the electrical activity generated by active muscle fibers and detected over the skin surface. sEMG signals are easy to record and offer significant access to the user's neuromuscular system. They provide information to detect muscle activation intervals and to study neural control strategies and neuromuscular system properties [20]. sEMG are considered an important source of information in many research fields such as neurophysiology, clinical medicine, biomechanics, movement analysis, ergonomics, space and sport sciences, and prosthetics. Recently, several architectures have been developed and tested to control robotic hands aimed at substituting parts of the body (e.g., hands or upper extremities). It is important to point out that in order to implement an EMG-based algorithm, the control of artificial limbs is complicated owing to the need to code the different actions of the artificial devices. In fact, it is usually not possible to use the "homologous" muscles to control the movements of the device, thus the development of a complex algorithm that exploits the potential of advanced movement recognition techniques is required [2]. In many cases, the formal scheme for the acquisition and analysis of EMG signals for the control of prosthetic devices is composed of several modules [21, 22]) such as, 1) signal acquisition (conditioning, pre-processing, and data segmentation); 2) decoding (feature extraction and pattern recognition); and 3) online control (actuation signal and degrees of freedom control) as shown in Figure 5.

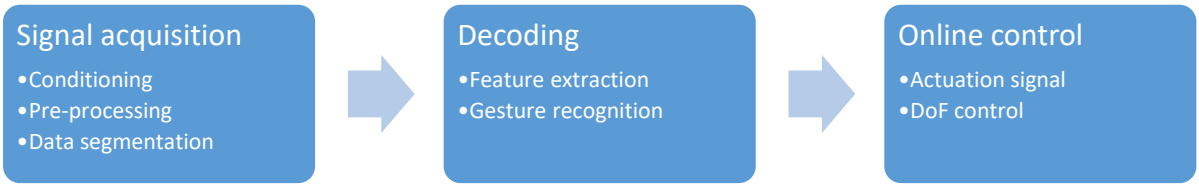


Figure 5. Steps in EMG control of robotic hands.

2.2 EMG control schemes

A wide variety of control schemes have been developed to translate the information in the EMG and are typically classified as – amplitude based control and feature based control. In general, the EMG signals are translated using the following schemes [5]: i. On–off control, ii. Proportional control, iii. Direct control, iv. Finite state machine control, v. Pattern recognition-based control, and vi. Regression control schemes. The amplitude based schemes (numbered i to iv) employ signal amplitude during muscular contraction to determine suitable activation threshold whereas feature-based schemes (numbered v to vi) use signal features based on time and frequency extraction and processing for movement recognition. The flowchart for implementation of different types of EMG schemes with signal processing stages is presented in Figure 6.

These control schemes are used either separately or in combination with multiple schemes. A detailed comparison of these control schemes is shown in Table 2. Most of the control schemes use EMG signals from either one or two muscle groups to determine a threshold value to control the myoelectric limb. In the case of one muscle group, varying intensity of muscular contractions are used to determine suitable activation thresholds that would trigger a particular action or 'state' of the end-effector. The amplitude-based methods

(e.g. on/off, direct, finite state machine control, etc.) allow actions such as slight contraction to close the hand, strong contraction to open, and no muscle activity to halt the device [30], as shown in Figure 7. The same technique could be applied to two opposing muscle groups, such as flexors and extensors, to control hand opening and closing [31]. Various thresholds can be used to determine which EMG activity is relevant and to discriminate from the background noise. Although both fast and applicable to real-time control, the number of movements generated is limited and the control is sequential in nature, unlike the smooth actions expected of the human hand [9]. Moreover, the number of movements generated by proportional and direct control systems is limited by the number of independently controllable EMG channels. As a result, current artificial end-effectors are mostly limited to such simple functions as generating power grip or elbow flexion/extension, far from the multifunctional control of the human arm.

Table 2. Comparison of various EMG control schemes.

Control scheme	Working principle	Advantages	Limitations
On-off [23]	Motor actuation with signal threshold value	Fast response; suitable for real-time control	Simple hand open or close functions; lack of multiple functions
Proportional [24, 25]	Voltage applied to motor proportional to signal intensity	Dexterity in control, suitable for gross movements	Used in combination with other control schemes; not suitable for fine movements
Direct [26]	Similar to proportional; involves multiple EMG sites	Individual control of multiple movements.	Difficult control due to muscle crosstalk
Finite state machine [27, 28]	Predefined postures of hand as states; transition among states decoded from input signals	Suitable for fixed number of postures	Not suitable for multi-functionality
Pattern recognition [6,7]	Extraction of features from signal; classification of segmented data to motor commands.	Identification of multiple movements; suitable for multifunctionality; intuitive control	Large processing times; not suitable for real-time control; sequential control; lack of simultaneous and proportional control; requires system training
Regression [8]	Similar to pattern recognition, involves regression analysis	Simultaneous control of multiple movements; intuitive control	Lack of robustness; high computation time and memory requirements

2.3 Factors of influence of EMG

The efficiency of signal interpretation of surface electromyography control depends upon a number of factors. Most myoelectric control schemes use macro-features (e.g. frequency, amplitude of electrical signal) of the surface EMG, that depend on the neural and peripheral information contained in the signal, their performance is influenced by the factors that can affect the motor unit action potential shapes or the neural drive to the muscle [14], [15]. The recorded surface action potentials are sensitive to electrode repositioning, changes in electrode-skin impedance (e.g., because of sweating), relative movement of the muscle with respect to the electrodes, including muscle fiber lengthening and shortening. Moreover, the distribution of action potential shapes varies greatly among subjects because of the anatomical variations in locations of the motor units within the muscle tissue. These factors influence substantially the performance of myoelectric control algorithms. Changes in electrode positioning or arm posture have a negative effect on the performance of myoelectric control methods [16–18].

Other important factors influencing surface EMG, which involve potential changes are fatigue, psychological factors, and in general any variability in the way a task is performed. Muscle crosstalk is another critical factor deteriorating system performance. It is defined as the signal recorded from a target muscle actually generated by other muscles in the vicinity. In some cases, the detected EMG signal is naturally the mixture of the activities of several muscles that are anatomically and functionally close, such as the forearm muscles, in which crosstalk is at least as large as the target muscle activity [19]. Other factors such as muscle depth and thickness, innervation zones, quality of skin contact, skin impedance, timing and intensity of muscle contractions all add variability to sEMG recordings [34].

2.4 Implications in multi-functional control

In order to improve the functionality of myoelectric end-effectors, in the past two decades, significant efforts have been invested in extracting additional neural control information from the surface EMG. These efforts have been mainly focused on feature-based methods such as pattern recognition and regression control. The pattern recognition algorithms, introduced in 1970s, assumes that distinct (separable) and consistent (repeatable) patterns can be derived from the surface EMG during different types of muscular contractions (motions). It provides multifunctional control by classifying different muscle activation patterns. These algorithms fundamentally include a sequence of events where the raw EMG data is first windowed, useful features are extracted and classified, before being used for control (Figure 8).

The development of these algorithms includes increasing the number of input channels which improved the accuracy of classifying features [32] and the resulting multifunctional control. This has allowed increased movement patterns to be classified beyond just grip, to include wrist flexion and extension, forearm pronation and supination, humeral rotation and ulnar and radial deviation at the wrist, with the current trend moving towards identifying muscle patterns to control individual fingers [9]. These control schemes require system training for effective classification of various movements. The training sets are generally collected in a constrained laboratory environment; whereas conditions may differ in actual unconstrained environment. Furthermore, pattern recognition methods inherently require sufficiently long

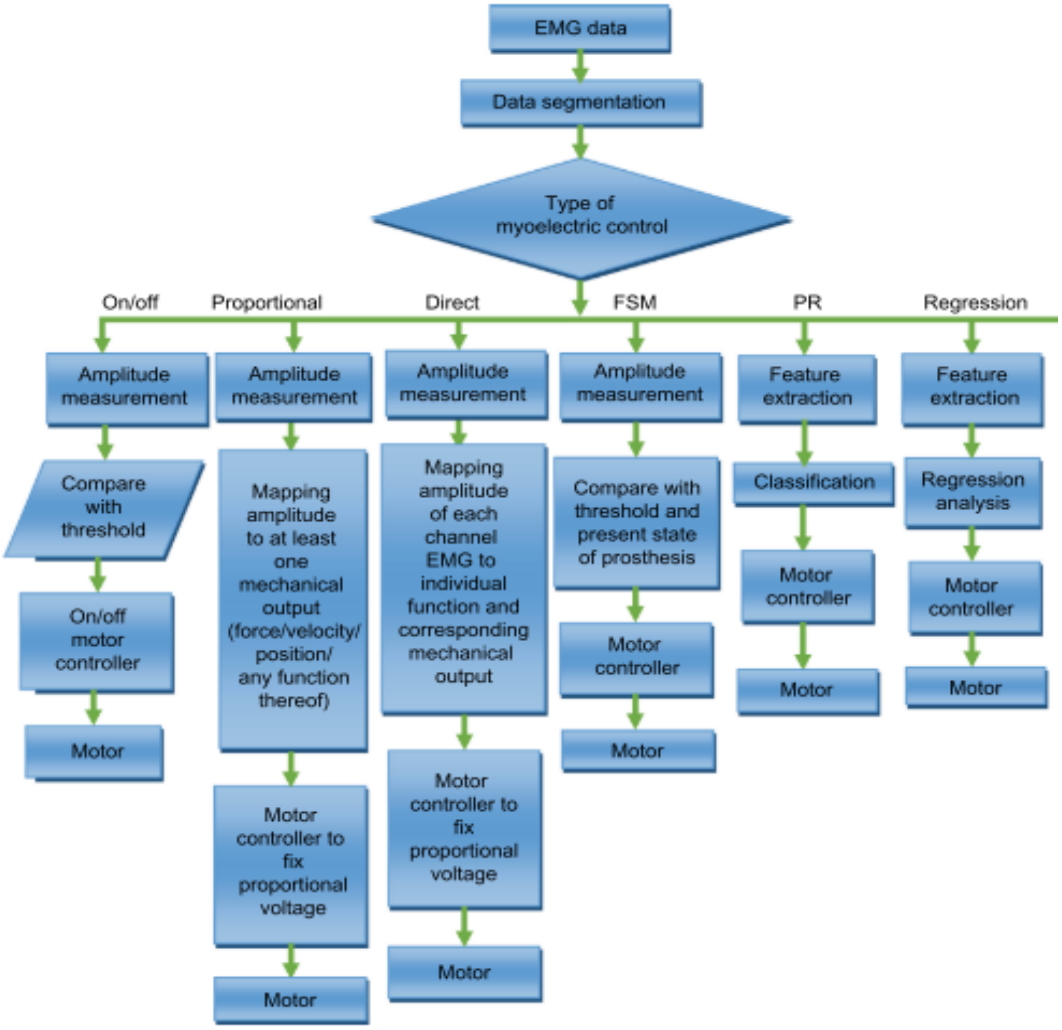


Figure 6. EMG control strategies [5].

intervals to extract useful classification features without delaying response time. This limits the real-time application of pattern-recognition control for robotic or prosthesis actuation [9]. Therefore, a robust system is preferable to one that is technologically complex and unreliable.

It is important to note that pattern recognition is only capable of classifying these movements in sequence and not simultaneously [10] as shown in Figure 8. The lack of reliable simultaneous control schemes is one of the major reasons for a gap between research and commercial applications [11]. Advanced applications of exoskeletons, teleoperation, and human–machine interfaces all require reliable simultaneous control of multiple DOFs, and have struggled to provide commercial applications [33].

3 Problem formulation and suggested solution

From the literature review presented in section 2, it is clear that current control schemes for myoelectric control of robotic end-effectors possess a number of limitations. These limitations affect the real-time online control of end-effectors. Following points are drawn from the literature review: -

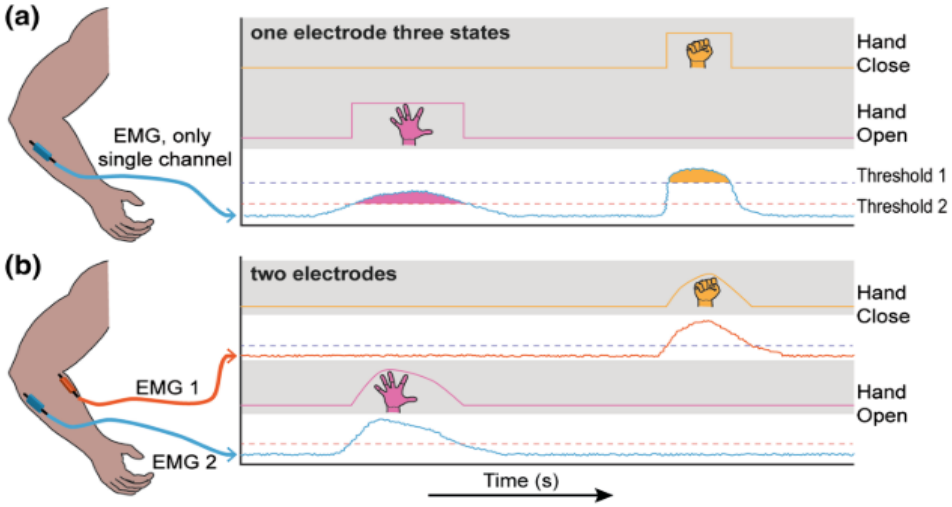


Figure 7. Amplitude-based control strategies [9].

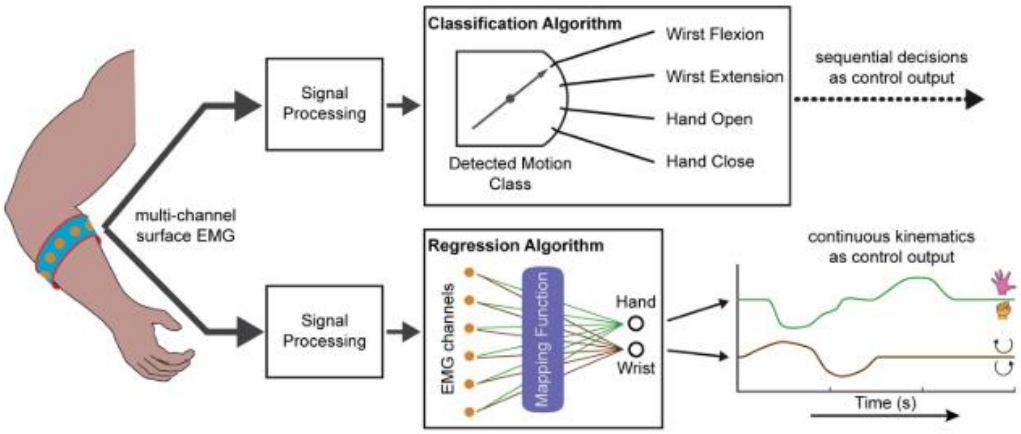


Figure 8. Feature-based control strategies [9].

- EMG control schemes, being noninvasive and providing ease of application, are affected by a number of factors during their application as mentioned in section 2.3. These dynamic factors reduce the efficiency and robustness required for controlling a robotic end-effector. Recently, research in the field of mechanomyography (MMG) has shown a potential alternative to EMG [12]. It is based on the principle that the gross lateral movement of the muscle causes measurable low frequency vibration in the muscle body during initial contraction. MMG is not subjected to physiological factors such as skin impedance, moisture level, etc. which enhance the real-time applicability of this scheme. Furthermore, the MMG sensors are easy to use [35, 36], and can be used for much longer than other sensors. They also allow classification of 'small' gestures, which has previously been problematic in similar systems. A hybrid control scheme will possess several potential benefits over conventional controls in terms of efficiency and robustness of control.
- The pattern recognition control enhances the functionality of control system by classifying multiple movement patterns from the input signal. Contrarily, the limitations of pattern recognition control such as lack of simultaneous and proportional

control, large computation time, hamper the real-time applicability as well as robustness of the system. On the contrary, recent developments in regression algorithms overcome the need to increase the complexity of the device whilst providing simultaneous and proportional control [9]. In contrast to methods only allowing classification of one motion at a time, regression algorithms are able to continuously estimate multiple control signals directly from the EMG signal (Figure 9b). Consequently, the regression approach provides greater flexibility for the user, leading towards a more intuitive control paradigm. Integrating conventional pattern recognition techniques with regression algorithms will enhance the functionality as well as classification accuracy for real-time online control of end-effectors.

Keeping in mind the above literature gaps, the proposed research work tends to address the concerning issues using recommended measures to analyze the spontaneity of an effective hybrid control scheme for robotic end-effectors. It is estimated to provide an efficient, robust, intuitive and real-time control scheme for performing a variety of manipulative actions.

4 Objectives

Following objectives have been set for the proposed research work: -

1. Kinematic analysis of an anthropomorphic robotic end-effector with underactuated mechanism.
2. Development of pattern recognition method in hybrid control scheme based on electromyography and mechanomyography for simultaneous control.
3. Performance analysis of hybrid control scheme based on electromyography and mechanomyography.
4. Integration of hybrid control scheme into robotic end-effector for functional assessment.

5 Methodology

The proposed research work will be performed as follows: -

- A robotic end-effector will be developed having anthropomorphic characteristics such as shape, size, movement, etc. The end-effector will be actuated through linkage/tendon underactuated mechanism working on DC motors and lithium-ion batteries. The underactuation mechanism will provide multiple degrees of freedom for the end-effector. The position, displacement, velocity, acceleration, linkage efficiency, etc. along with strength of structural members of the proposed end-effector will be analyzed through simulation.
- A hybrid control scheme will be developed based on electromyography (EMG) and mechanomyography (MMG). These assistive techniques will allow to compensate for the limitations of EMG caused due to physiological factors. The input signal from a test user will be subjected to pattern recognition techniques to identify user intention. The pattern recognition scheme will employ a feature extraction algorithm and a classification algorithm to identify the intended motion command by the user. The

classification algorithm will consist of artificial neural networks (ANN) for user intent identification. The entire control scheme and required algorithms will be developed in MATLAB® programming language and will be deployed onto a controller board.

- Experiments will be performed on different users to validate the performance of the proposed hybrid control scheme in terms of various performance indices such as classification accuracy, segmentation accuracy, completion time, error rate, etc. Effect of various process variables will be studied during performance analysis of the proposed control scheme such as signal energy, consistency of gestures, user fatigue, electrode efficiency, electrode shift, muscle crosstalk, transient changes in EMG, etc. The performance of the proposed hybrid control scheme will be compared with other control schemes presented in literature for validation purposes.
- The proposed hybrid control scheme will be integrated into the proposed anthropomorphic end-effector. The functions of both software and hardware configurations will be mapped and synchronized with each other. Various functional/experimental assessment tests for the robotic end-effector in a constrained environment will be performed to determine the effectiveness of the proposed hybrid control scheme.

5.1 Work plan

The research work will be carried out in following steps as shown in Table 3:-

Table 3. Comparison of various EMG control schemes.

Activity	Months									
	1 - 3	4 - 6	7 - 9	10 - 12	13 - 15	16 - 18	19 - 21	22 - 24	25 - 27	28 - 30
Literature review										
Hypothesis development										
Research design										
Hybrid control scheme development										
Validation										
Experimentation										
Results										
Analysis										
Thesis writing										

6 References

[1] D. Farina, N. Jiang, H. Rehbaum, A. Holobar, B. Graimann, H. Dietl, O.C. Aszmann, The extraction of neural information from the surface EMG for the control of upper-limb prostheses: Emerging avenues and challenges, IEEE Trans. Neural Syst. Rehabil. Eng. 22 (2014) 797–809. doi:10.1109/TNSRE.2014.2305111.

[2] S. Micera, J. Carpaneto, S. Raspopovic, Control of hand prosthesis using peripheral information, Biomed. Eng. IEEE Rev. 3 (2010) 48–68.

[3] N. Jiang, S. Dosen, K.-R. Muller, D. Farina, Myoelectric Control of Artificial Limbs - Is There a Need to Change Focus?, IEEE Signal Process. Mag. (2012).

[4] E. Scheme, K. Englehart, Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use, J. Rehabil. Res. Dev. 48 (2011) 643. doi:10.1682/JRRD.2010.09.0177.

[5] P. Geethanjali, Myoelectric control of prosthetic hands: State-of-the-art review, Med. Devices Evid. Res. 9 (2016) 247–255. doi:10.2147/MDER.S91102.

[6] G. Li, A.E. Schultz, T.A. Kuiken, Quantifying pattern recognition- based myoelectric control of multifunctional transradial prostheses, IEEE Trans. Neural Syst. Rehabil. Eng. 18 (2010) 185–192. doi:10.1109/TNSRE.2009.2039619.

[7] A.J. Young, L.H. Smith, E.J. Rouse, L.J. Hargrove, Classification of simultaneous movements using surface EMG pattern recognition, IEEE Trans. Biomed. Eng. 60 (2013) 1250–1258. doi:10.1109/TBME.2012.2232293.

[8] G. Purushothaman, K.K. Ray, EMG based man-machine interaction - A pattern recognition research platform, Rob. Auton. Syst. 62 (2014) 864–870. doi:10.1016/j.robot.2014.01.008.

[9] A.D. Roche, H. Rehbaum, D. Farina, O.C. Aszmann, Prosthetic Myoelectric Control Strategies : A Clinical Perspective, Curr Surg Rep. 2 (2014). doi:10.1007/s40137-013-0044-8.

[10] N. Jiang, I. Vujaklija, H. Rehbaum, B. Graimann, D. Farina, Is accurate mapping of EMG signals on kinematics needed for precise online myoelectric control?, IEEE Trans. Neural Syst. Rehabil. Eng. 22 (2014) 549–558. doi:10.1109/TNSRE.2013.2287383.

[11] M. Ison, P. Artemiadis, The role of muscle synergies in myoelectric control: Trends and challenges for simultaneous multifunction control, J. Neural Eng. 11 (2014). doi:10.1088/1741-2560/11/5/051001.

[12] S. Wilson, R. Vaidyanathan, Upper-limb prosthetic control using wearable multichannel mechanomyography, IEEE Int. Conf. Rehabil. Robot. (2017) 1293–1298. doi:10.1109/ICORR.2017.8009427.

[13] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Miller, K. A. Stubblefield, and K. B. Englehart, "Targeted muscle reinnervation for real-time myoelectric control ofmultifunction artificial arms," JAMA, vol. 301, no. 6, pp. 619–628, Feb. 2009.

[14] D. Farina, R. Merletti, and R. M. Enoka, "The extraction of neural strategies from the surface EMG: An update," J. Appl. Physiol., 2014, accepted for publication.

[15] D. Farina, R. Merletti, and R. M. Enoka, "The extraction of neural strategies from the

surface EMG," J. Appl. Physiol., vol. 96, no. 4, pp. 1486–1495, Apr. 2004.

[16] A. J. Young, L. J. Hargrove, and T. A. Kuiken, "The effects ofelectrode size and orientation on the sensitivity of myoelectric pattern recogni- tion systems to electrode shift," IEEETrans. Biomed. Eng., vol. 58, no. 9, pp. 2537–2544, Sep. 2011.

[17] E. Scheme, A. Fougner, Ø. Stavdahl, A. D. Chan, and K. Englehart, "Examining the adverse effects oflimb position on pattern recognition basedmyoelectric control," in Proc. Annu. Int. Conf. IEEEEngineering in Medicine and Biology Soc. (EMBC2010), 2010, pp. 6337–6340.

[18] A. Fougner, E. Scheme, A. D. C. Chan, K. Englehart, and O. Stavdahl, "Resolving the limb position effect in myoelectric pattern recognition," IEEE Trans. Neural Rehabil. Syst. Eng., vol. 19, no. 6, pp. 644–651, Dec. 2011.

[19] S. Muceli, N. Jiang, and D. Farina, "Extracting signals robust to elec- trode number and shift for online simultaneous and proportional myoelectric control by factorization algorithms," IEEE Trans. Neural Re- habil. Syst. Eng., 2014, accepted for publication.

[20] D. Farina, R. Merletti, and R. M. Enoka, "The extraction of neural strategies from the surface EMG," J. Appl. Physiol., vol. 96, no. 4, pp. 1486–1495, 2004.

[21] M. Zecca, S. Micera, M. Carrozza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," Crit. Rev. Biomed. Eng., vol. 30, no. 4–6, pp. 459–485, 2002.

[22] M. Oskoei and H. Hu, "Myoelectric control systems—A survey," Biomed. Signal Proc. Contr. J., vol. 2, pp. 275–294, 2007.

[23] Almstrom C. An electronic control system for a prosthetic hand with six degrees of freedom, Tech. Rep. 1:77, Research Laboratory of Medical Electronics, Chalmers University of Technology; 1977.

[24] Bottomley AH, Wilson ABK, Nightingale A. Muscle substitutes and myo-electric control. J Br Inst Radio Eng. 1963;26(6):439–448.

[25] Sörbye R. Myoelectric controlled hand prostheses in children. Int J Rehab Res. 1977;1:15–25.

[26] Hahne JM, Biessmann F, Jiang N, et al. Linear and nonlinear regres- sion techniques for simultaneous and proportional myoelectric control. IEEE Trans Neural Syst Rehabil Eng. 2014;22(2):269–279.

[27] Kyberd PJ, Holland OE, Chappel PH, et al. MARCUS: a two degree of freedom hand prosthesis with hierarchical grip control. IEEE Trans Rehab Eng. 1995;3:70–76.

[28] Cipriani C, Zaccone F, Micera S, Carrozza MC. On the shared control of an EMG-controlled prosthetic hand: analysis of user-prosthesis interaction. IEEE Trans Robot. 2008;24(1):170–184.

[29] Segil JL, Weir RF. Design and validation of a morphing myoelectric hand posture controller based on principal component analysis of human grasping. IEEE Trans Neural Syst Rehabil Eng. 2014;22(2): 249–257.

[30] BattyeCK,NightingaleA,Whillis J. Theuse ofmyo-electric currents in the operation ofprostheses. J Bone Joint Surg Br. 1955;37:506–10.

http://web.jbjs.org.uk/cgi/content/abstract/37-B/3/506.

[31] Popov B. The bio-electrically controlled prosthesis. J Bone Joint Surg Br. 1965;47:421–4. http://www.bjj.boneandjoint.org.uk/ content/47-B/3/421.abstract.

[32] Kuruganti U, Hudgins B, Scott RN. Two-channel enhancement of a multifunction control system. IEEE Trans Biomed Eng. 1995;42:109–11. http://www.ncbi.nlm.nih.gov/pubmed/7851924.

[33] Singh R M, Chatterji S and Kumar A 2012 Trends and challenges in EMG based control scheme of exoskeleton robots—a review Int. J. Sci. Eng. Res. 3 933–40.

[34] Ahmad I, Ansari F and Dey U 2012 A Review of EMG recording technique Int. J. Eng. Sci. Technol. 4 530–9.

[35] S. Wong, "Man with no limbs controls robotic hand using muscle whispers," in New Scientist, 2015.

[36] A. H. S.O.H. Madgwick, R. Vaidyanathan, "An efficient orientation filter for IMU and MARG sensor arrays," in Report, Department of Mechanical Engineering, University of Bristol, 2010.